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Optimizing Cost Performance in Green Industrial Palm Oil Projects Using AI-Based AEC

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Abstract. This study investigates green industrial palm oil project cost performance determinants through Artificial Intelligence (AI)-based Architecture, Engineering, and Construction (AEC) systems. The study employed a Structural Equation Modeling Partial Least Squares (SEM-PLS) approach to analyze significant data collected from 115 respondents through 166 validated indicators. Ten primary drivers were identified, and alternative water sources topped the list, followed by indoor air quality auditing, green material, and smart metering systems, all of which were identified as primary cost-effectiveness drivers. Simulations of Green Mark certification levels (Gold, Gold Plus, and Platinum) indicated potential cost savings of 7.01% to 7.05%. The model continued to have very good predictive capability with an R^2 value of 0.791, testifying to the robustness of the methodology presented. The results validate the engineering value of AI-aided AEC in cost performance maximization and enhancement in eco-friendly industrial building. The findings also offer practical suggestions for design, planning, and execution of cost-saving, eco-friendly palm oil mills.

Keywords: AI-based AEC, cost performance, green industry, palm oil mill, SEM-PLS

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1. Introduction

The palm oil industry is one of the major drivers of Indonesia's economy, with a national Gross Domestic Product (GDP) contribution of 3.76% in 2022. It supplies domestic and export markets for cooking oil, biodiesel, and others product [1]. In the meantime, the industry is also a major driver of environmental problems such as greenhouse gas emissions and deforestation, necessitating the adoption of development practices in line with green industry principles [2]. The green industry concept aims to minimize environmental effects by utilizing improved energy efficiency and reduced emissions, in line with global directions of sustainable industrial and construction development. Indonesian industrial area development was initiated under Presidential Decree No. 53 of 1989, which set the foundation for green industry development.

The integration of Artificial Intelligence (AI)-based Architecture, Engineering, and Construction (AEC) practice offers encouraging prospects to increase energy efficiency, promote cost performance, and reduce environmental effects in the palm oil sector [3,4]. A number of the key drivers of green industry practice include energy efficiency, wastewater treatment, and water conservation, which are essential given Indonesia's relatively low environmental performance. The 2024 Environmental Performance Index (EPI) ranked Indonesia 162nd out of 180 countries with a score of 33.80, necessitating environmental policy reform and green construction practices [5].

The World Emissions Clock 2024 reports the construction sector emits 3.2 gigatons of CO_2 worldwide out of a total of 58.9 gigatons. In Indonesia, the construction sector contributes approximately 24.9 million tons of CO_2 annually [6]. These figures indicate the sector's importance in achieving emission reduction and energy conservation targets. The concept of green building focuses on reducing energy and carbon emissions throughout the life cycle of a building, from design and construction to demolition.

The incorporation of green space and sustainable design also enables carbon sequestration, while water resource conservation remains a critical component [7]. Aligned with the Sustainable Development Goals (SDGs), the integration of AEC and green technologies can increase cost-effectiveness and promote industrial sustainability towards 2030 [8]. Proper integration of green technologies can reduce energy consumption by 30% to 80%. However, investment in green buildings tends to be higher than in conventional projects by around 5%, primarily due to management, labor, and certification expenses. Within the palm oil industry, AI-powered AEC can potentially integrate industrial building design and construction in terms of cost and energy efficiency [3].

Previous research has demonstrated the beneficial effect of technology adoption on green building project cost performance. Waqar et al. [9] confirmed the use of Building Information Modeling (BIM) and intelligent construction technologies to improve cost and time efficiency in infrastructure projects. Pratama et al. [10] showed that integrating green building design with smart energy management systems can enhance energy efficiency by up to 25%. Kyivska and Tsiutsiura [11] identified building orientation and optimization of the building envelope design as factors for reducing energy consumption, while Kim and Park [12] and Pham et al. [13] stated that building envelope optimization can reduce energy loads by 50% and automated HVAC systems by 20%. Chaudhuri et al. [14] emphasized the importance of designing energy-efficient infrastructure for reducing industrial waste. Prasetyawan et al. [15], through Structural Equation Modeling–Partial Least Squares (SEM-PLS), identified cost uncertainty and fiscal incentives as significant drivers of green building implementation.

Husin and Priyawan [16] and Husin et al. [17] applied SEM-PLS combined with Blockchain-BIM in Indonesian green retrofitting projects, which led to improved cost effectiveness and lifecycle value. Yu et al. [18] promoted adaptive energy efficiency standards that evolve with technological advancements. Istri et al. [19] also demonstrated through SEM analysis that the adoption of green construction practices enhances cost performance, quality outcomes, and environmental sustainability. The objective of this study is to identify the most important factors that affect cost performance in green palm oil industrialization development through the utilization of AI-based AEC technologies. The study also intends to examine the real-world implementation of these technologies to identify their potential in reducing construction costs and improving operational effectiveness.

2. **Methods**

This study adopted an Action Research approach, with the central goal of raising the sustainability of palm oil industrial complexes through innovative, sustainable design and construction processes, and reducing associated environmental impacts. The study model comprised one dependent variable, cost effectiveness, and three independent variables: Palm Oil Mill (X1), Green Industry (X2), and Architecture, Engineering, and Construction (AEC) (X3).

Primary data were obtained through direct observation and structured questionnaires administered to selected respondents. Both variables and indicators were developed from existing literature and system-based interactions observed in the studied industrial estates [20]. Secondary data were obtained from academic journals, official reports, books, and other credible publications to improve theoretical analysis and verify primary findings [21].

Data collection techniques included semi-structured, in-depth interviews with key informants, direct observation of project-related phenomena, and documentation through field notes and photographs. All data were organized systematically by variables and sub-factors using Microsoft Excel.

Data were analyzed using the Structural Equation Modeling Partial Least Squares (SEM-PLS) method [22], selected for its suitability in modeling complex relationships between latent variables and for its capability with relatively small sample sizes. In the research of green building, SEM-PLS is most effective when used in combination with value engineering and lifecycle cost analysis (LCCA) to optimize environmental and cost performance [23]. The process of analysis involved model specification based on theory, testing for model fit, inputting data using covariance or correlation matrices, and assessing goodness-of-fit. Subsequently, the responses were screened, and variables were measured using a six-point Likert scale (1 = Strongly Disagree, 6 = Strongly Agree) for hypothesis testing.

3. Results and Discussion

3.1 Preliminary Data Analysis

Expert interviews were conducted during the initial data collection to validate and refine the indicators. This process led to the elimination of 46 redundant indicators from the initial 211, leaving 166 valid indicators that were grouped into 19 dimensions and four primary latent variables. Responses from 115 respondents were analyzed through a focus on the SEM–PLS approach, providing four primary variable models (Table 1).

Table 1. Main Structural Path Modeling of SEM-PLS

Variable Manifest/ Indicator	Latent Variable	Primary Construct
X1.1.1 – X1.1.12	Planning (X1.1)	Palm Oil Mill (X1)
X1.2.1 – X1.2.5	Contract Tender (X1.2)	
X1.3.1 – X1.3.6	Project Management (X1.3)	
X1.4.1 – X1.1.18	Construction (X1.4)	
X1.5.1 – X1.5.16	Operational & Maintenance (X1.5)	
X2.1.1 – X2.1.10	Energy Efficiency (X2.1)	Green Industry (X2)
X2.2.1 – X2.2.9	Water Efficiency (X2.2)	
X2.3.1 – X2.3.17	Sustainable Construction & Management (X2.3)	
X2.4.1 – X2.4.17	Smart and Healthy Building (X2.4)	
X2.5.1 – X2.6.13	Green Features and Innovations (X2.5)	
X3.1.1 – X3.1.6	Machine Learning (X3.1)	Architecture Engineer Construction Architecture Engineering Construction (AEC) (X3)
X3.2.1 – X3.1.6	Computer Vision (X3.2)	
X3.3.1 – X3.3.6	Automated Planning and Scheduling (X3.3)	
X3.4.1 – X3.4.6	Robotics (X3.4)	
X3.5.1 – X3.5.5	Knowledge-based systems (X3.5)	
X3.6.1 – X3.6.4	Natural Language processing (X3.6)	
X3.7.1 – X3.7.4	Optimisation (X3.7)	
Y1.1.1 – Y1.1.4	Internal (Y1.1)	Cost (Y)
Y1.2.1 – Y1.2.2	External (Y2.2)	

3.2 Outer Model Test

The outer model test confirmed the reliability and validity of the measurement model. All outer loading values were greater than 0.50, exhibiting good convergent validity. Average Variance Extracted (AVE) values were also above the 0.50 benchmark. Cronbach's Alpha and Composite Reliability values were all ≥ 0.70, indicating high internal consistency between constructs.
For ease of readability, the complete indicator-level validity and reliability estimates, like outer loadings, Cronbach's Alpha, Composite Reliability, and AVE values, are presented in Appendix A (Tables A1–A2). In short, the Green Industry construct proved to be the most reliable (Cronbach's Alpha = 0.986), followed closely by Palm Oil Mill (0.985) and Architecture, Engineering, and Construction (AEC) (0.982).

Figure 1 indicates the path coefficients of the structural model, and Figure 2 and Figure 3 indicate the measures of reliability and discriminant validity. These confirm that the measurement instruments effectively discriminate between constructs and maintain conceptual uniqueness.

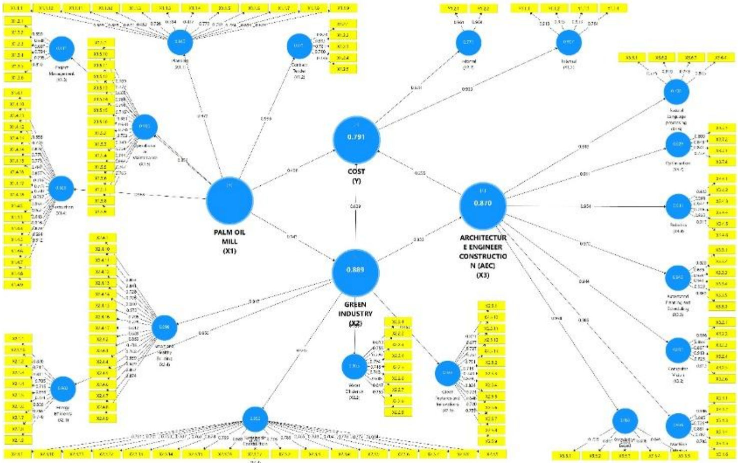

Figure 1. SEM-PLS Path Coefficients

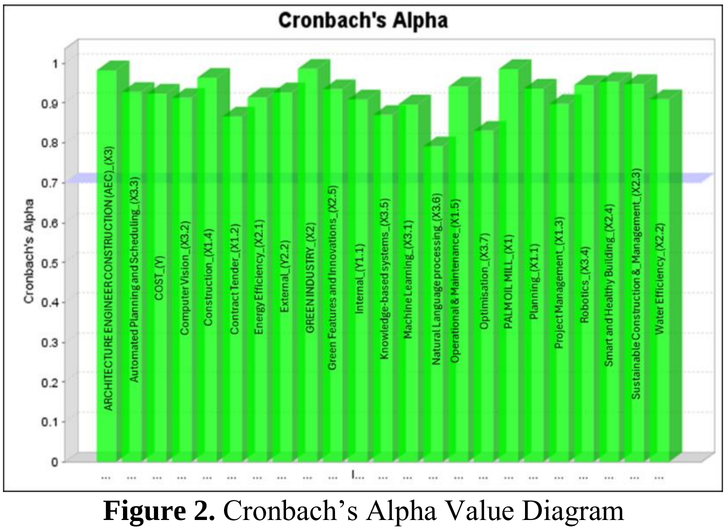

Figure 2. Cronbach's Alpha Value Diagram

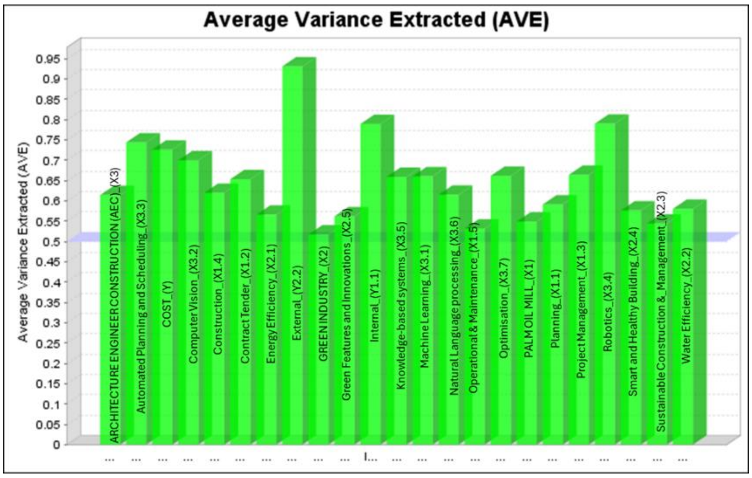

Figure 3. Average Variance Extracted (AVE) Diagram

The coefficient of determination (R^2) for the Cost Performance construct reached 0.791 (Adjusted R^2 = 0.785), indicating that approximately 79.1% of the variance is explained by the independent variables, with the remainder attributable to other factors. Several constructs achieved notably high explanatory power, including Automated Planning and Scheduling (R^2 = 0.940) and Construction (R^2 = 0.928), suggesting their substantial influence on overall model performance (see Appendix, Table A3)

3.3 Inner Model Analysis

The results of the model indicate that the variable Cost Performance (Y) had an R^2 value of 0.791 (Adjusted R^2 = 0.785), therefore Palm Oil Mill, Green Industry, and AEC constructs explain 79.1% variation. This is a satisfactory explanatory power in engineering management research. Predictive relevance (Q^2) testing resulted in $Q^2 > 0$ for all endogenous variables, and this is a confirmation of the power to predict with the model. Effect size (f^2) test revealed the largest effect of Green Industry on Cost Performance (f^2 = 0.42), followed by AEC (f^2 = 0.35), and then Palm Oil Mill (f^2 = 0.28), representing large, medium, and medium effects, respectively. The GoF index of the model was 0.72, indicating a very strong overall fit to applied engineering practice.

The significance of all the path coefficients obtained through the bootstrapping technique is depicted in Figure 4, which reveals strength and direction of causality between constructs. The SEM–PLS green industrial cost performance model, which was R^2 = 0.825 when Q^2 and f^2 were included to verify it. The lower R^2 for this present model is balanced by a broader range of indicators, thereby thereby enhancing its generalizability to industrial settings in green humid tropical climates.

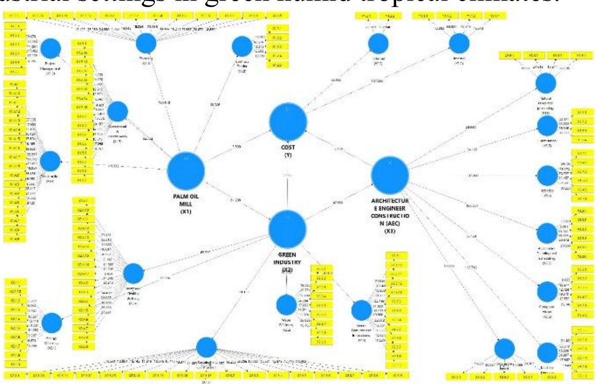

Figure 4. Bootstrapping Result

3.4 Key Factor Analysis
Factor ranking identified ten most important drivers of cost performance improvement for achieving BCA Green Mark certification (Platinum and Gold levels). They are: advanced monitoring technologies, alternative water supplies, green materials, indoor air quality audits, smart metering systems, and solar-ready roofs (Table 2).

Table 2. Top Ten Factors Affecting Green Industrial Cost Performance

No	Sub Factor		Original Sample	Mean	T Statistics >1,96 (p< 0,05)	In Relation to R Square
1	Alternative Water Sources	X2.2.8	0,8171	0,8157	28,9744	
2	Indoor Air Quality (IAQ) Surveillance Audit	X2.4.3	0,8629	0,8610	28,8570	
3	Power Usage Effectiveness (PUE)	X2.1.1	0,8196	0,8169	26,0819	
4	Green Materials	X2.3.5	0,7597	0,7619	22,6955	
5	Solar Ready Roof	X2.1.9	0,7704	0,7711	19,0364	
6	Private meters to measure the water consumption at the cooling tower make-up water tank.	X2.2.5	0,7476	0,7450	18,6210	**0,791**
7	Smart remote metering system with alert features for leak detection and monitoring purposes.	X2.2.6	0,7478	0,7422	15,0430	
8	Data Centre Infrastructure Management (DCIM)	X2.4.5	0,7678	0,7616	14,2396	
9	Lighting Quality and Management	X2.4.4	0,7384	0,7288	12,1187	
10	Recycling Facilities	X2.3.17	0,7061	0,7006	10,4281	

The use of energy efficiency measures as the most highly ranked driver underscores their critical role in reducing operational expenses and environmental impacts. Optimizing the building envelope alone is to reduce energy consumption by 50% [24], and advanced HVAC automation can achieve an additional 20% reduction [25]. The integration of AI-based AEC technology complements these gains through enabling predictive maintenance, real-time monitoring, and automated resource allocation.

Compared to previous research, the present findings confirm the relevance of infrastructure quality, working practices, and adaptability in adjusting to evolving green standards [26-28]. For example, the integration of predictive analytics and smart systems significantly improved cost and energy performance in green industrial buildings.

3.5 Practical Implications
The results provide practical implications for policymakers, engineers, and industry professionals:

- Policy Synergy: Incentive structures should be in place to encourage investment in green features of high impact such as renewable energy readiness and self-monitoring systems.
- Engineering Optimization: Value engineering together with SEM–PLS modelling offers a sound approach to establishing cost–benefit priorities in green industrial initiatives.

- Sustainability Alignment: The model supports sustainable industrial transformation through the balancing of technical efficiency and cost performance in accordance with certification schemes.

4. Conclusion

This study identified ten key factors with the greatest influence on the improvement of cost performance in the green industrial development of palm oil using Artificial Intelligence (AI)-based Architecture, Engineering, and Construction (AEC). They include alternative sources of water, indoor air quality monitoring, power efficiency consumption, green building materials, and smart metering. The adoption of AI-based AEC strategies was found to be highly cost-saving, with simulations across various Green Mark certification levels (Gold, Gold Plus, and Platinum) yielding potential savings between 7.01% and 7.05%. The findings confirm that AI-based AEC enhances not only the technical efficacy of construction activities but also the strategic capacity to develop a sustainable and competitive palm oil industry.

Based on these, it is recommended that government agencies develop policies, rules, and special incentives for promoting the adoption of Green Industry principles in Palm Oil Mills (POMs). Implementation of these practices offers obvious benefits to stakeholders, including reduced consumption of raw materials, energy, and water, as well as reduced production of waste and emissions. Furthermore, this research also provides a reference model for the extension of green industry principles to other industries, the development of more sustainable and economically successful industries.

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Appendix

Table A1. Outer Loading Value (Convergent Validity)
The table reveals the outer loading values of each indicator to establish convergent validity. All indicators are greater than the minimum value (>0.50), indicating high construct validity.

No	Indicator	Outer Loading Value	Validity S > 0,5
1	X1.1.1	0,714	valid
2	X1.1.2	0,680	valid
3	X1.1.3	0,691	valid
4	X1.1.4	0,803	valid
5	X1.1.5	0,787	valid
6	X1.1.6	0,694	valid
7	X1.1.7	0,762	valid
8	X1.1.8	0,786	valid
9	X1.1.9	0,632	valid
10	X1.1.10	0,867	valid
11	X1.1.11	0,860	valid
12	X1.1.12	0,639	valid
13	X1.2.1	0,868	valid
14	X1.2.2	0,843	valid
15	X1.2.3	0,724	valid
16	X1.2.4	0,674	valid
17	X1.2.5	0,641	valid
18	X1.3.1	0,871	valid
19	X1.3.2	0,866	valid
20	X1.3.3	0,667	valid
21	X1.3.4	0,752	valid
22	X1.3.5	0,766	valid
23	X1.3.6	0,777	valid
24	X1.4.1	0,850	valid
25	X1.4.2	0,765	valid
26	X1.4.3	0,809	valid
27	X1.4.4	0,816	valid
28	X1.4.5	0,692	valid
29	X1.4.6	0,768	valid
30	X1.4.7	0,856	valid
31	X1.4.8	0,694	valid
32	X1.4.9	0,612	valid
33	X1.4.10	0,704	valid
34	X1.4.11	0,859	valid
35	X1.4.12	0,718	valid

No	Indicator	Outer Loading Value	Validity S > 0,5
84	X2.3.8	0,777	valid
85	X2.3.9	0,684	valid
86	X2.3.10	0,701	valid
87	X2.3.11	0,753	valid
88	X2.3.12	0,707	valid
89	X2.3.13	0,760	valid
90	X2.3.14	0,678	valid
91	X2.3.15	0,793	valid
92	X2.3.16	0,689	valid
93	X2.3.17	0,760	valid
94	X2.4.1	0,863	valid
95	X2.4.2	0,689	valid
96	X2.4.3	0,863	valid
97	X2.4.4	0,738	valid
98	X2.4.5	0,768	valid
99	X2.4.6	0,859	valid
100	X2.4.7	0,629	valid
101	X2.4.8	0,867	valid
102	X2.4.9	0,874	valid
103	X2.4.10	0,841	valid
104	X2.4.11	0,728	valid
105	X2.4.12	0,706	valid
106	X2.4.13	0,680	valid
107	X2.4.14	0,673	valid
108	X2.4.15	0,705	valid
109	X2.4.16	0,729	valid
110	X2.4.17	0,612	valid
111	X2.5.1	0,819	valid
112	X2.5.2	0,713	valid
113	X2.5.3	0,740	valid
114	X2.5.4	0,824	valid
115	X2.5.5	0,824	valid
116	X2.5.6	0,724	valid
117	X2.5.7	0,648	valid
118	X2.5.8	0,720	valid

No	Indicator	Outer Loading Value	Validity S > 0,5
36	X1.4.13	0,707	valid
37	X1.4.14	0,712	valid
38	X1.4.15	0,839	valid
39	X1.4.16	0,775	valid
40	X1.4.17	0,714	valid
41	X1.4.18	0,716	valid
42	X1.5.1	0,709	valid
43	X1.5.2	0,735	valid
44	X1.5.3	0,703	valid
45	X1.5.4	0,749	valid
46	X1.5.5	0,759	valid
47	X1.5.6	0,744	valid
48	X1.5.7	0,664	valid
49	X1.5.8	0,767	valid
50	X1.5.9	0,765	valid
51	X1.5.10	0,772	valid
52	X1.5.11	0,665	valid
53	X1.5.12	0,788	valid
54	X1.5.13	0,798	valid
55	X1.5.14	0,716	valid
56	X1.5.15	0,681	valid
57	X1.5.16	0,633	valid
58	X2.1.1	0,820	valid
59	X2.1.2	0,811	valid
60	X2.1.3	0,705	valid
61	X2.1.4	0,715	valid
62	X2.1.5	0,658	valid
63	X2.1.6	0,721	valid
64	X2.1.7	0,809	valid
65	X2.1.8	0,756	valid
66	X2.1.9	0,770	valid
67	X2.1.10	0,741	valid
68	X2.2.1	0,813	valid
69	X2.2.2	0,755	valid
70	X2.2.3	0,729	valid
71	X2.2.4	0,794	valid
72	X2.2.5	0,748	valid
73	X2.2.6	0,748	valid
74	X2.2.7	0,688	valid

No	Indicator	Outer Loading Value	Validity S > 0,5
119	X2.5.9	0,795	valid
120	X2.5.10	0,677	valid
121	X2.5.11	0,727	valid
122	X2.5.12	0,761	valid
123	X2.5.13	0,751	valid
124	X3.1.1	0,846	valid
125	X3.1.2	0,845	valid
126	X3.1.3	0,726	valid
127	X3.1.4	0,881	valid
128	X3.1.5	0,787	valid
129	X3.1.6	0,782	valid
130	X3.2.1	0,666	valid
131	X3.2.2	0,883	valid
132	X3.2.3	0,887	valid
133	X3.2.4	0,919	valid
134	X3.2.5	0,828	valid
135	X3.2.6	0,813	valid
136	X3.3.1	0,820	valid
137	X3.3.2	0,635	valid
138	X3.3.3	0,939	valid
139	X3.3.4	0,943	valid
140	X3.3.5	0,929	valid
141	X3.3.6	0,869	valid
142	X3.4.1	0,923	valid
143	X3.4.2	0,900	valid
144	X3.4.3	0,947	valid
145	X3.4.4	0,706	valid
146	X3.4.5	0,923	valid
147	X3.4.6	0,913	valid
148	X3.5.1	0,709	valid
149	X3.5.2	0,861	valid
150	X3.5.3	0,830	valid
151	X3.5.4	0,806	valid
152	X3.5.5	0,845	valid
153	X3.6.1	0,775	valid
154	X3.6.2	0,810	valid
155	X3.6.3	0,746	valid
156	X3.6.4	0,805	valid
157	X3.7.1	0,809	valid

No	Indicator	Outer Loading Value	Validity S > 0,5
75	X2.2.8	0,817	valid
76	X2.2.9	0,759	valid
77	X2.3.1	0,761	valid
78	X2.3.2	0,736	valid
79	X2.3.3	0,785	valid
80	X2.3.4	0,765	valid
81	X2.3.5	0,708	valid
82	X2.3.6	0,704	valid
83	X2.3.7	0,770	valid

No	Indicator	Outer Loading Value	Validity S > 0,5
158	X3.7.2	0,843	valid
159	X3.7.3	0,841	valid
160	X3.7.4	0,757	valid
161	Y1.1.1	0,913	valid
162	Y1.1.2	0,933	valid
163	Y1.1.3	0,933	valid
164	Y1.1.4	0,764	valid
165	Y1.2.1	0,961	valid
166	Y1.2.2	0,969	valid

Table A2. Cronbach's Alpha, Composite Reliability, and Average Variance Extracted (AVE)
This table summarizes the reliability and validity statistics for each latent construct. All constructs demonstrate Cronbach's Alpha and Composite Reliability values ≥0.70, and AVE ≥0.50, confirming internal consistency and convergent validity.

	Cronbach's Alpha	**rho_A**	**Composite Reliability**	**Average Variance Extracted (AVE)**
ARCHITECTURE ENGINEER CONSTRUCTION *Architecture Engineering Construction* (AEC)**_(X3)**	**0,982**	**0,983**	**0,983**	**0,615**
Automated Planning and Scheduling_(X3.3)	0,927	0,939	0,945	0,744
COST_(Y)	**0,924**	**0,926**	**0,941**	**0,726**
Computer Vision_(X3.2)	0,913	0,924	0,933	0,700
Construction_(X1.4)	0,963	0,966	0,967	0,620
Contract Tender_(X1.2)	0,866	0,879	0,904	0,654
Energy Efficiency_(X2.1)	0,914	0,915	0,928	0,566
External_(Y2.2)	0,926	0,933	0,964	0,931
***GREEN INDUSTRY*_(X2)**	**0,986**	**0,986**	**0,986**	**0,517**
Green Features and Innovations_(X2.5)	0,934	0,936	0,943	0,562
Internal_(Y1.1)	0,909	0,917	0,937	0,790
Knowledge-based systems_(X3.5)	0,870	0,880	0,906	0,659
Machine Learning_(X3.1)	0,896	0,903	0,921	0,661
Natural Language processing_(X3.6)	0,791	0,794	0,865	0,615
Operational & Maintenance_(X1.5)	0,941	0,943	0,948	0,532
Optimisation_(X3.7)	0,830	0,842	0,887	0,662
PALM OIL MILL_(X1)	**0,985**	**0,986**	**0,986**	**0,549**
Planning_(X1.1)	0,936	0,940	0,945	0,592
Project Management_(X1.3)	0,897	0,904	0,922	0,664
Robotics_(X3.4)	0,945	0,950	0,957	0,790

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Smart and Healthy Building_(X2.4)	0,953	0,953	0,958	0,577
Sustainable Construction &_Management_(X2.3)	0,947	0,948	0,953	0,544
Water Efficiency_(X2.2)	0,909	0,911	0,926	0,581

Table A3. Coefficient of Determination (R^2) and Adjusted R^2 for Latent Variables
This table provides the coefficient of determination (R^2) and adjusted R^2 values for each latent variable in the structural model, reflecting the model's explanatory power.